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Does a Scopic Regime Produce Conformism? Herding Behavior among Trade Leaders on Social Trading Platforms *

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Abstract

Social trading platforms (STPs) are transparent online markets governed by a scopic regime, where order flow is publicly disclosed and participants are subject to constant reciprocal scrutiny. Participants on STPs can be categorized into trade leaders and copiers, where the former execute unique trades and manage the funds allocated to them by the latter in return for compensation. Given limited individual capacity and the competition to attract copiers, we investigate whether the scopic regime produces excess and perpetual conformism among trade leaders. Using data from a popular STP, and from an anonymous traditional foreign exchange broker, we show that the scopic regime produces excess levels of herding. Under the scopic environment, we find that herding is high when market information is scarce, which is evidence of herding due to informational cascades. We find herding to be relatively low among risk-seeking trade leaders, which may be a sign of overconfidence. Herding is high for larger trades, suggesting that traders herd to avoid the disappointment associated with underperforming on large positions. Finally, we show that herding in the scopic environment persists at much higher levels compared to traditional environments. Our findings indicate that exposure to a scopic information-rich environment augments the limitations and personal biases of individual traders, thus producing excess and perpetual herding.

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1 Introduction

A common phenomenon that has been documented in behavioral finance literature is that individuals have a tendency to herd, thus accumulating on the same side of the market. Herding behavior occurs when investors make the same decisions, either by intentionally mimicking others' investment strategies, or unintentionally as a result of acting on common information. While the latter type of herding is seen as a result of efficient markets, intentional herding has the potential to increase volatility and destabilize markets (Hirshleifer and Hong Teoh, 2003). This is due to the fact that individual investors who follow the crowd, also referred to as noise traders, have the capacity to affect asset prices since their correlated actions are systematic (Barber et al., 2009). In recent years, the notion of herding has been capitalized on by many brokerage firms, and incorporated into online trading, thus resulting in a new trading environment known as social trading.

Social trading is a novel concept that combines online trading with the tools provided by social media platforms, the result of which is a highly transparent trading marketplace known as a social trading platform (STP), where traders come together to communicate, collaborate on research tasks and trading strategies, and even *explicitly* copy each others' trading activities in real-time using a mirror trading algorithm. This environment requires complete disclosure from participants regarding their real-time portfolio holdings and historical trading activities. Hence, STPs are governed by what is known as a "scopic regime", a novel concept introduced in the field of *social* finance, which designates a state of permanent reciprocal observation and scrutiny (Knorr Cetina, 2003). We adopt this term in an interdisciplinary fashion in order to distinguish the trading environment on STPs from the traditional trading environments. Participants in a scopic environment do not observe each other directly but can see the outcome of each other's actions through the order flow. Consequently, participants are judged based on their actions, and are cognitively positioned in a hierarchy of status levels. One manifestation of this concept is the categorization of STP participants into two main groups: trade leaders and copiers, where the former presumably includes experienced traders of a superior status who manage the funds allocated to them by the latter in return for monetary compensation. Trade leaders compete to attract potential copiers by signaling their status as leaders, which is attained by executing original trades. In other words, entering unique trades into the STP signifies that the trader is knowledgeable, skilled, and confident enough not to resort to explicit copying. Copiers can simply click a button to copy a single trade or all future trades of a certain trade leader, and do not need to intervene except for terminating this copying relationship. Moreover, copiers can diversify their investments across multiple trade leaders with different trading styles in aim of decreasing their overall portfolio volatility. It is important to note that the copier still has the authority to modify the terms of a copied trade, such as adding a stop-loss level, in which case the trade is still considered to be copied. It follows that a trade is considered to be unique (i.e. not *explicitly* copied) only in the case where it has been personally entered by a trader into the trading platform. Moreover, the relationship between trade leaders and copiers is largely informal, as there are no official sanctions should a trade leader go rogue, deviate from his advertised strategy, or lose his copiers' money.

STPs are based on the notion of complete disclosure of order flow data, which can be particularly valuable to traders in the foreign exchange market, where studies have shown that *private* order flow data of both retail investors (Nolte and Nolte, 2012, 2016) and institutional investors (Marsh and O'Rourke, 2005; Lyons, 2001; Goodhart, 1988; Lyons, 1997) contains significant genuine information that can be used to forecast exchange rates.[1] The importance of having easy access to detailed order flow information for financial decision making is further accentuated by the fact that there are infrequent announcements of fundamental data by central banks, and erratic global economic and political events that stimulate foreign exchange markets in a random way. Hence, given the fast-paced environment of electronic trading, the limited capacity of individual traders to analyze the entire asset universe available to them (Barber and Odean, 2008; Odean, 1999), the ease of access to (what was

[1] We refer to literature that focuses on the foreign exchange market since the data sets used in this study predominantly contain currency trades.

once privileged) detailed order flow data, and the aspiration to jump-start a career as a money manager — with virtually no setup costs or penalties should things go awry — to earn performance compensation, traders may be highly tempted to avoid conducting their own analysis and making trading decisions, and simply imitate others. This can be achieved by personally entering orders similar to those of other trade leaders after they are publicly disclosed on the STP. Consequently, we expect that the competition to attract copiers in the scopic environment would augment the limitations and personal biases of trade leaders, thus producing excess and perpetual localized herding as traders continuously rely on public order flow as a steady source of information.

Nevertheless, under traditional financial theory, the efficient market hypothesis — even in its weakest form — postulates that given an environment with high information transparency, asset prices should reflect all publicly disclosed information (Fama, 1998). Hence, despite the fact that STPs facilitate the imitation of past trading activities, herding behavior should erode (especially in the long term), as the information contained in publicly disclosed order flow data would already be incorporated into prices. Moreover, individual retail traders in the foreign exchange market are not expected to possess superior private (fundamental) information. Hence, rational trade leaders would realize this and abstain from herding with each other.

Given the lack of research on this novel phenomenon, we aim to investigate whether the scopic regime augments the limitations and biases of individual traders, thus inducing higher localized levels of and persistence in herding compared to those found in traditional trading environments. To the best of our knowledge, this is the first paper to investigate herding behavior of 1) traders in a scopic environment, and 2) traders in the foreign exchange markets at the individual level in a traditional trading environment. We use two unique proprietary data sets: the first is obtained from a popular STP, which we call SocialEx that is governed by a scopic environment and includes over 2.6 million transactions executed by 77,476 trade leaders during 2013, and the second from a traditional online foreign exchange broker, which we call TradEx, and includes around 6.9 million transactions executed by 22,545 retail traders between 2011 and 2013. Since most trades on SocialEx are in currencies, and thus the results would not be directly comparable to the literature, which focuses on equity traders, we use TradEx as a control group in order to highlight the impact of the scopic environment on herding behavior. Data limitations do not allow us to examine and compare comparable subgroups of traders on the two trading platforms. Nevertheless, given the global popularity of SocialEx, and the lack of literature on retail foreign exchange traders suggesting variations in herding behavior arising from different demographic populations, we work on the assumption that traders on both platforms come from similar demographic distributions. In other words, traders on the two platforms are assumed to inherently have similar propensities towards herding; thus any difference in herding levels between the two platforms can be attributed to the effect of the trading environment. We adopt several herding measures and techniques, including those developed by Lakonishok et al. (1992) (LSV henceforth), Frey et al. (2014) (FHW henceforth), Merli and Roger (2013), Sias (2004), and Barber et al. (2009) in order to estimate herding among traders in the different trading environments. We conduct the analyses using quarterly, monthly, weekly, and daily data frequencies.

In general, we find that the overall level of herding under the scopic regime on SocialEx is significantly higher compared to the results obtained for traders on TradEx and in other traditional trading environments. Furthermore, we estimate herding for different sub-samples based on trading intensity, leverage, and trade size. First, we find that herding among trade leaders is relatively high when market information is scarce, and that this phenomenon is absent among traders on TradEx. This suggests that the scopic environment encourages traders to seek information from the trades of others in securities that have less market information, resulting in herding due to informational cascades (Bikhchandani et al., 1992). Second, we find herding to be relatively low among risk-seeking trade leaders, which is in line with the literature that risk takers are overconfident in their own decisions. Third, we show that herding increases as investment size increases, and that this gradually occurs over time as individuals apprehend the disappointment associated with underperforming on large positions, thus increasing the likelihood of following the general consensus. In addition, trade leaders use small-sized trades in an experimental fashion to mimic potentially profitable strategies of others. Finally, we find that herding in the scopic environment persists across several time periods at much higher levels, and fades away much slower compared to herding in traditional environments. This shows the added herding impact that the scopic regime produces given the limitations and biases of individual investors to analyze many assets in a highly dynamic environment. In summary, all our findings suggest that the excess perpetual herding produced by the scopic environment is intentional. However, further research is required on the predictive power of publicly disclosed order flow data in order to determine whether the excess herding under a scopic regime is rational or simply driven by behavioral biases.

Our findings call attention to several implications within the locale of scopic trading environments. From a macro perspective, as STPs increase in popularity and the number of traders choosing to herd grows, asset prices would deviate from their fundamental value and trades would become increasingly correlated, resulting in heightened market volatility. Moreover, the high degree of conformity on STPs can have serious consequences for copiers who diversify their investments across trade leaders, since it results in higher correlation among trading strategies, which in turn diminishes the volatility-reduction benefits obtained from diversification.

The remainder of this paper is organized as follows. Section 2 covers the theoretical and empirical literature on herding behavior. Section 3 presents the herding measures and techniques used. In section 4, we present the two data sets along with key descriptive statistics. Section 5 is dedicated to the discussion of the results. The final section recaps the findings and highlights some of the implications arising from herding on STPs.

2 Literature Review

To the best of our knowledge, this is the first paper to examine herding behavior in a social trading context, and compare it to herding among individual foreign exchange traders in a traditional financial setting. Given the lack of relevant literature in these two areas, we refer to some of the most popular theoretical and empirical studies conducted on institutional as well as individual equity investors in a traditional environment.

2.1 Theoretical Literature

Recent finance theory differentiates between intentional, and unintentional or spurious herding; however, such a task is very difficult to do in practice. Intentional herding is driven by sentiment and entails the explicit imitation of the activities of others, which may lead to inefficient markets where prices fail to reflect fundamental information, in addition to increased volatility and destabilization of markets (Hirshleifer and Hong Teoh, 2003). Nonetheless, several researchers have proposed theories and models portraying intentional herding as a rational behavior. For instance, models on informational herding are based on the notion that reliable market information is scarce. The possibility that some investors are more knowledgeable about the market may motivate a less informed investor to try and infer information from past or even current trades of others, leading to informational cascades (Bikhchandani et al., 1992; Welch, 1992). Another branch of literature rationalizes intentional herding as a consequence of institutional schemes such as reputation and compensation. For example, Maug and Naik (2011) find that remuneration packages may give fund managers an incentive to herd, especially when the amount of compensation received is based on performance relative to a benchmark. Similarly, Scharfstein and Stein (1990) and Dasgupta and Prat (2008) examine the relationship between reputation and herding, and show that managers would sacrifice the potential to generate high returns as a trade-off against not tarnishing their reputation due to relative underperformance. Finally, a third reason why intentional herding may arise is due to weak market regulation or concentrated ownership (Borensztein and Gelos, 2003; Viet et al., 2008; Oehler et al., 2008).

On the other hand, unintentional herding is mainly caused by investors acting on the same or highly correlated information, which may be due to common behavioral biases, leading them to arrive at similar trading decisions (Hirshleifer et al., 1994). Barber et al. (2009) conduct a study on individual investors and argue that coordinated trading is primarily driven by three behavioral factors. The first is representativeness heuristics, where investors with similar beliefs about an asset's performance persistence are likely to trade the same asset. This argument echoes the work of Tversky and Kahneman (1974) and De Bondt (1993), who argue that investors tend to make decisions where they expect the distribution of a small sample or short time series to be representative of that of the population. Moreover, Falkenstein (1996) argues that managers may share a preference towards assets with specific risk or liquidity characteristics. The second factor is investor attention, whereby individual investors do not have the capacity to analyze all assets available to them for investment, and may simply focus on the ones that are currently in the news spotlight or have caught their attention (Barber and Odean, 2008; Odean, 1999). Finally, the third factor is the disposition effect, where investors tend to avoid the regret related to selling losing investments, thus sell winning ones instead. As such, herding arises when investors sell an asset that has recently increased in value. Overall, we can identify two main categories of explanatory factors that induce herding behavior: institutional, and cognitive-psychological.

2.2 Empirical Literature

Measuring herding behavior can be difficult in practice (Bellando, 2012). Nonetheless, LSV presented a simple statistic to empirically estimate correlated trading among investors, which has since become a standard measure of herd behavior. The LSV measure analyzes the aggregate buying pressure on a specific asset for a group of traders over a period of time. LSV apply their measure to U.S. equity pension fund managers and find an overall mean herding level of 0.027. The following quote by LSV (1992: p. 30) aids in the understanding of how this figure is interpreted:

> "...it implies that if p, the average fraction of changes that are increases, was 0.5, then 52.7% of the money managers were changing their holdings of an average stock in one direction and 47.3% in the opposite direction."

Many empirical studies on herding among institutional investors have been based on the seminal work of LSV. For instance, Grinblatt et al. (1995) use a sample of 274 mutual funds from 1974 to 1984 and find weak evidence of herding with a mean LSV measure of 2.5%. Similarly, Graham (1999) and Wermers (1999) use more recent samples of U.S. mutual funds and report slightly higher herding levels. In contrast to the U.S. market, researchers have estimated herding to be higher in emerging markets and several European markets such as in Germany (Walter and Moritz Weber, 2006; Frey et al., 2014; Kremer and Nautz, 2013), the U.K. (Wylie, 2005), France (Arouri et al., 2013), Poland (Voronkova and Bohl, 2005), and Portugal (Lobao and Serra, 2007). The higher level of herding in these markets is attributed to the stage of development of the financial system (Walter and Moritz Weber, 2006; Oehler et al., 2008), ambiguous information (Lobao and Serra, 2007), highly concentrated stock ownership (Viet et al., 2008), or weak market regulation (Borensztein and Gelos, 2003). While the evidence in the literature shows that herding varies across countries and exchanges (Griffin et al., 2003), Gebka and Wohar (2013) find that it is virtually non-existent when studied at the international level. LSV state that in the market as a whole, one cannot detect herding since there is an equal number of assets bought and sold. Hence, herding can only be examined within subgroups of investors.

For instance, LSV and Voronkova and Bohl (2005) find more pronounced herding in small-cap stocks. Since market capitalization is often used as a proxy for the amount and quality of information available, higher herding levels in small-cap stocks is interpreted as evidence of intentional herding when information is scarce. This finding is in line with the theory of information availability discussed by Wermers (1999), whereby investors are more likely to herd in situations where there is very little market information. Opposing evidence is presented by FHW, who use both the LSV measure as well as their proposed herding measure, and find a decreasing relationship as well as below average herding levels for smaller stocks based on the LSV measure. However, they find that the number of fund managers active in a stock is positively related to market capitalization. Consequently, one should expect higher herding estimates for larger stocks due to the lower bias. The FHW measure, on the other hand, shows a u-shaped relationship with a higher level of herding for the smallest stocks. The study by Merli and Roger (2013) on individual investors also shows evidence of higher herding levels for large market capitalization stocks; however, this result is not obtained for all quarterly periods and is not robust when using the FHW measure.

Several studies examine herding behavior in relation to trading intensity by progressively increasing the minimum threshold for the number of transactions in each asset. For instance, Grinblatt et al. (1995), Wylie (2005), Merli and Roger (2013), and FHW report stronger evidence of herding in sub-samples with a high trading intensity. On the other hand, Wermers (1999) finds little variation in the level of herding across the different thresholds for trading intensity. The author shows that herding decreases to just over 3% as trading intensity increases to more than 50 funds, and notes that the highest trading activity is found in large-cap stocks, which exhibit lower levels of herding. As such, the author argues that increasing the minimum threshold of trade intensity implicitly changes the sample to larger and more liquid stocks, which may overshadow any increase in herding that might arise from a larger number of funds active in the stocks.

Another branch of literature focuses on herding behavior among individual investors. Using daily transactions of more than 37,000 individual investors at a German discount broker from 1998 to 2000, Dorn et al. (2008) report a mean LSV estimate of 8.3%. The authors argue that the high level of herding appears to be primarily driven by correlated speculative motives. Moreover, a study performed by Barber et al. (2009) uses two data sets, the first composed of 66,465 investors obtained from a discount broker, and the second containing 665,544 investors at a retail broker. The authors report LSV herding measures of 6.81% and 12.79%, respectively for these data sets. Finally, Merli and Roger (2013) use a sample of 87,373 French retail investors obtained from a major European broker house from 1999 to 2006, and report higher herding levels compared to previous studies.

The general consensus in the literature is that herding among individual investors is higher compared to institutional investors, and that this higher level is attributed to individual psychological as well as cognitive factors. While these studies examine herding under traditional trading environments, the scopic regime governing STPs raises the following questions. What happens when retail traders find themselves in an environment that embraces the free flow of information and encourages social interactions? Does the social aspect of the STP unveil the personal biases of individuals and their limited analytical capacity, such that the scopic environment induces an additional herding effect? We expect that such a trading environment will encourage higher perpetual herding among trade leaders as a mechanism for preserving their status.

3 Methodology

3.1 The LSV Herding Measure

The LSV measure (HLSV henceforth) estimates herding, which occurs when the proportion of traders in a given asset trading in the same direction (buying or selling) is greater than the proportion of traders in the entire asset universe that are in that direction under the null hypothesis that trading decisions are independent. The HLSV measure can be expressed as:

$$HLSV_{i,t} = |\pi_{i,t} - \hat{\pi}_t| - \underbrace{E\left[\left|\frac{\tilde{b}_{i,t}}{n_{i,t}} - \hat{\pi}_t\right| ; \tilde{b}_{i,t} \sim B(\hat{\pi}_t, n_{i,t})\right]}_{AF_{i,t}} \tag{1}$$

where $\pi_{i,t} = b_{i,t}/n_{i,t}$ is the buy proportion of traders, such that $b_{i,t}$ is the number of traders buying, and $n_{i,t}$ is the total number of active traders in security i during period t. The parameter $\hat{\pi}_t = \frac{\sum_{i=1}^{\mathbb{I}} b_{i,t}}{\sum_{i=1}^{\mathbb{I}} n_{i,t}}$ is the average proportion of traders buying relative to the total number of active traders in the entire asset universe $\mathbb{I}$ in period t, which is also the expected probability of being a buyer under the null hypothesis of no herding. Since the first term on the right in Equation (1) will be positive even under the null hypothesis (due to the stochastic nature of trades), the second term, $AF_{i,t}$, is an adjustment factor that corrects for this expected dispersion. The adjustment factor allows for random variation around $\hat{\pi}_t$ under the null hypothesis of independent trading decisions, and is the expected value of the left-hand term in Equation (1), when the number of buyers $\tilde{b}_{i,t}$ is binomially distributed with probability $\hat{\pi}_t$ and $n_{i,t}$ independent draws. The overall degree of herding behavior is measured by averaging $HLSV_{i,t}$ across all security-periods, i, t. A positive and significant HLSV measure indicates the existence of herding behavior.

The HLSV measure has been criticized by many academics in the literature because it suffers from several drawbacks. First, FHW and Bellando (2012) demonstrate that under the alternative hypothesis of herding, the HLSV measure has a positive value in expectations, resulting in a downward bias relative to the true herding measure that increases with the level of herding. However, these two studies show that the bias decreases as the number of active traders in the asset during the period increases. While ignoring the adjustment factor in the HLSV measure would overstate the true herding level, including it results in an over-correction of the excess dispersion, leading to a downward bias. To overcome this issue, FHW propose an alternative measure of herding behavior, which they claim is an unbiased and consistent estimate of the true level of herding. Second, the HLSV measure does not allow us to identify intertemporal changes in herding behavior. While we are able to study how investors herd in a given security over time, this measure does not permit us to examine whether it is the same individuals that continue to herd in that asset. Merli and Roger (2013) propose an alternative herding measure, called the Investor

Herding Measure, which examines herding at the individual level. Finally, Bikhchandani and Sharma (2000) argue that the LSV measure captures both intentional and unintentional herding. Differentiating between these two types of herding behavior is crucial since the latter is an expected product of an efficient market, while the former has the potential of increasing volatility and destabilizing markets. As such, Sias (2004) presents a dynamic approach that differentiates between traders who follow their own trades, and traders who follow the trades of others, which he argues is the *true* herding behavior of individuals. In what follows, we present these alternative herding measures.

3.2 The FHW Herding Measure

FHW propose an alternative measure (labeled HFHW henceforth), which they argue is a consistent estimate of the true herding level. The rationale behind this measure is similar to that of the HLSV, in the sense that it calculates the excess dispersion of trades on either side of the market (buy or sell). The HFHW measure can be written as:

$$\mathbb{H}_{i,t}^2 = \frac{(b_{i,t} - \hat{\pi}_t n_{i,t})^2 - n_{i,t}\hat{\pi}_t(1-\hat{\pi}_t)}{n_{i,t}(n_{i,t}-1)}, \tag{2}$$

where $\hat{\pi}_t$ is the average proportion of traders buying relative to the total number of active traders in the entire asset universe $\mathbb{I}$ in period t. In addition, $b_{i,t}$ is the number of traders buying and $n_{i,t}$ is the total number of active traders in security i during period t, such that $\pi_{i,t}$ is the proportion of buyers.

The $\mathbb{H}^2$ measure is averaged across securities and periods to obtain an estimate of the overall herding behavior. Let the set of all security-periods i, t be denoted by $\mathcal{A}$. It follows that the aggregated measure of herding can be written as:

$$\mathbb{H}_{\mathcal{A}}^2 = \frac{1}{\#\mathcal{A}} \sum_{i,t\in\mathcal{A}} \mathbb{H}_{i,t}^2. \tag{3}$$

In order to make the aggregated herding measure comparable to the HLSV, the square root of the overall herding value is taken as follows:

$$HFHW_{\mathcal{A}} \equiv \sqrt{\mathbb{H}^2_{\mathcal{A}}}. \tag{4}$$

While HLSV is biased under the alternative hypothesis of herding, but performs well under the null hypothesis, the opposite is true for HFHW. FHW argue that given a small number of traders n, HFHW would exhibit a downward bias which stems from the non-linearity of taking the square root of the unbiased estimator $\mathbb{H}^2$.

One criticism of the HFHW measure is that it is only unbiased in the particular environment considered by the authors, where $\hat{\pi} = 0.5$. Bellando (2012) argues that when the probability of no herding is not null, HFHW exhibits an upward bias, which arises when aggregating the $\mathbb{H}^2$ measure across all security-periods. While it is practically impossible to compute the true herding level, the author shows that this value is bounded by the lower HLSV estimate and the upper HFHW estimate.

3.3 The Investor Herding Measure (IHM)

The HLSV and HFHW measures estimate herding at the security level, thus only allowing us to study how traders herd in a certain security during a period of time. Thus, these measures do not indicate whether it is the same individuals who are herding within the same security. Merli and Roger (2013) address this by introducing an alternative measure called the Investor Herding Measure (IHM), which only considers herding for the securities traded by the trader.

Similar to Grinblatt et al. (1995) and Wermers (1999), we differentiate between buy herding ($\pi_{i,t} > \hat{\pi}_t$) and sell herding ($\pi_{i,t} < \hat{\pi}_t$), and write the signed HLSV measure as:

$$SLSV_{i,t} = \begin{cases} HLSV_{i,t} \mid \pi_{i,t} > \hat{\pi}_t \\ \\ -HLSV_{i,t} \mid \pi_{i,t} < \hat{\pi}_t \end{cases} = \begin{cases} \pi_{i,t} - \hat{\pi}_t - AF_{i,t} \\ \\ \pi_{i,t} - \hat{\pi}_t + AF_{i,t} \end{cases} \tag{5}$$

Given Equation (5), each transaction may be assigned to one of six potential scenarios:

	Buying	Selling
SLSV > 0	Herding	Anti-Herding
SLSV < 0	Anti-Herding	Herding
SLSV = 0	No Herding	No Herding

When the trader trades only one asset, estimating herding behavior is relatively simple. For instance, a trader who trades only one security will have a herding value equal to the SLSV estimate of that security if the position is a buy, and to -SLSV if the position is a sell. Once a trader becomes active in multiple assets, measuring herding behavior becomes much more complex. Merli and Roger (2013) propose weighing the herding value in a security by the size of the trade, and the sum of the weighted herding measure is subsequently divided by the sum of the trades of the trader during the period. The IHM can be written as:

$$IHM_{j,t} = \frac{\sum_{i=1}^{\mathbb{I}} (n_{i,j,t} - n_{i,j,t-1}) \overline{P}_{i,t} SLSV_{i,t}}{\sum_{i=1}^{\mathbb{I}} |n_{i,j,t} - n_{i,j,t-1}| \, \overline{P}_{i,t}}, \tag{6}$$

where $\overline{P}_{i,t}$ is the average price at which security i is bought or sold over the period $[t, t{-}1]$, and the term $(n_{i,j,t} - n_{i,j,t-1})\overline{P}_{i,t}$ is the average value of the trades in security i. The denominator in Equation (6) is the sum of the values of all trades made by trader j during the period. A positive IHM means that the trader exhibits herding behavior, while a negative value suggests anti-herding behavior.

3.4 The Sias Herding Measure

HLSV and HFHW are static measures that estimate contemporaneous herding within the same time period. Sias (2004) proposed a dynamic approach that examines whether a trader's tendency to buy an asset persists over time. The Sias measure is based on the standardized buyer ratio, which is expressed as:

$$\Delta_{i,t} = \frac{\pi_{i,t} - \hat{\pi}_t}{\sigma(\pi_{i,t})}, \tag{7}$$

where $\sigma(\pi_{i,t})$ is the cross-sectional standard deviation of the buyer ratios across i securities during time t. The Sias herding measure, which we denote by $SIAS_{full}$, is estimated by computing the correlation between the standardized buyer ratios in two consecutive periods. This can be done by estimating a cross-sectional regression for each period t as:

$$\Delta_{i,t} = \beta_t \Delta_{i,t-1} + \epsilon_{i,t}, \tag{8}$$

and then calculating the time-series average of the β coefficients. A high buyer ratio typically suggests a high HLSV estimate; however, it does not necessarily imply a high $SIAS_{full}$ estimate, since the latter depends on the buyer ratio at the subsequent trading day.

Furthermore, Sias (2004) differentiates between individuals who follow their own trades, $SIAS_{own}$, and individuals who follow the trades of others, $SIAS_{other}$. The author argues that the latter captures the *true* herding behavior of individuals. Formally, the Sias measure can be decomposed into these two components:

$$\begin{aligned} \beta = \rho(\Delta_{i,t}, \Delta_{i,t-1}) = &\left[\frac{1}{(I-1)\sigma(\pi_{i,t})\sigma(\pi_{i,t-1})}\right] \sum_{i=1}^{I} \left[\sum_{n=1}^{N_{i,t}} \frac{(D_{n,i,t} - \hat{\pi}_t)(D_{n,i,t-1} - \hat{\pi}_{t-1})}{N_{i,t} N_{i,t-1}}\right] \\ &+ \left[\frac{1}{(I-1)\sigma(\pi_{i,t})\sigma(\pi_{i,t-1})}\right] \sum_{i=1}^{I} \left[\sum_{n=1}^{N_{i,t}} \sum_{m=1, m\neq n}^{N_{i,t-1}} \frac{(D_{n,i,t} - \hat{\pi}_t)(D_{m,i,t-1} - \hat{\pi}_{t-1})}{N_{i,t} N_{i,t-1}}\right], \end{aligned} \tag{9}$$

where $N_{i,t}$ is the number of traders trading security i during time t, and I is the number of securities traded. $D_{n,i,t}$ is a binary variable that takes the value of one if trader n is a net buyer in security i during time t, and zero otherwise. $D_{m,i,t-1}$ is a binary variable that takes the value of one if trader m, where $m \neq n$, is a net buyer during time $t-1$. Thus, the first component in Equation (9) represents the portion of the cross-sectional inter-temporal correlation that stems from traders following their own strategies due to buying or selling the same security over two consecutive trading periods. The second component in the equation represents the portion of the correlation that arises due to traders following the trades of others in a previous adjacent period. Sias (2004) argues that a positive correlation that results from traders following others can be interpreted as evidence of informational cascades.

3.5 Testing for Persistence in Herding

In our final analysis, we adopt an approach similar to that applied by Barber et al. (2009) to test whether traders' decisions are correlated across different trading periods. We examine the persistence in herding such that persistence exists if the autocorrelation of purchase intensities $\pi_{i,t}$ is high. In other words, a high (low) purchase intensity in asset i at time t is followed by a high (low) purchase intensity in future periods.

To conduct this analysis, we divide the data set into two equally sized random groups of traders, labeled G_1 and G_2, respectively. For each of the two groups, we calculate the purchase intensities for every asset during each period t, which are denoted by $\pi_{i,t}^{G_1}$ and $\pi_{i,t}^{G_2}$, respectively. We subsequently calculate the contemporaneous correlations between the purchase intensities, resulting in a time-series of correlations for each time period. If the traders' trading decisions are independent, then no correlation between $\pi_{i,t}^{G_1}$ and $\pi_{i,t}^{G_2}$ is expected. To test this hypothesis, we calculate the average mean contemporaneous correlation, followed by a test of significance to check whether the correlation is different from zero. Barber et al. (2009) explain that the null hypothesis of no correlation between the purchase intensities is synonymous to the null hypothesis of no herding behavior when applying the HLSV and

HFHW measures. While this analysis does not allow us to differentiate between intentional and unintentional herding, it simply indicates whether trading decisions are correlated.

Next, we measure the degree of persistence in herding behavior by calculating the correlations between the purchase intensities at time t and $t + \tau$ — due to space limitations we only report the results where $\tau = 1 \rightarrow 11$ for monthly periods, and $\tau = 1 \rightarrow 40$ for weekly and daily periods. Recall that the contemporaneous correlations to test the null hypothesis of no herding are obtained by setting $\tau = 0$. When $\tau > 0$, then the degree of persistence in herding behavior is computed. For example, by setting $\tau = 1$, the correlation between the purchase intensities between period t and the consecutive period $t + 1$ is computed. This calculation is repeated with different values for τ, and is conducted on each of the two random groups of traders, separately. Moreover, this calculation is also applied to both groups together, such that we compute the correlations between the purchase intensities of the first group of traders G_1 at time t, and those of the second group G_2 at time $t + \tau$.

4 Data

We use two unique proprietary data sets where the first is obtained from a popular STP, which we call SocialEx, and the second from a traditional online retail foreign exchange broker, which we call TradEx.

The data limitations in this paper do not allow us to identify and examine comparable subgroups of traders on the two platforms. However, given the global popularity of SocialEx, and the lack of literature on retail foreign exchange traders suggesting potential differences in herding behavior due to demographic characteristics, we work on the assumption that traders on both platforms come from similar demographic distributions. Consequently, traders on both platforms are assumed to inherently have similar propensities towards herding. This implies that the variation in herding levels between the two platforms can be attributed to the effect of the trading environment. Moreover, we are unable to thoroughly investigate the relation between herding and trader performance, such as return on investment, due to the lack of information on trader balances in our data sets. To illustrate, a profit of one unit for a trader with a balance of 10 units equals a return of 10%, whereas the same amount of profit for a trader with a balance of 100 units translates into a return of 1%. We highlight this data limitation as a potential opportunity for future research.

4.1 SocialEx Data

The first data set is obtained from SocialEx, one of the largest and most popular STPs, and contains over 63 million transactions executed by all participants during 2013. SocialEx offers traders a wide range of assets from several markets, including currencies, commodities, and equities. Participants on SocialEx do not trade the actual asset, but instead open a position through a standardized contract for difference (CFD) that is written on the asset. A CFD is an electronic contract between a trader and a broker (the CFD provider), whereby the trader forgoes physical ownership of the underlying asset for a contract with the broker that provides the same economic exposure (Norman, 2009). CFDs are essentially derivative instruments that allow traders to gain exposure and speculate on the direction of the underlying asset, without the need of ownership. These contracts are traded on margin, thus permitting highly leveraged positions. The STP records the details of each CFD transaction, including the opening and closing prices, the amount bought or sold, the leverage used, the direction, as well as the time-stamp of each trade. Since this study is focused on the herding behavior among trade leaders, we apply a strict criterion where we only select traders whose transactions were all personally entered into the STP during 2013 (i.e. those who did not explicitly copy others using mirror trading).[2] It is important to note that many traders can have a mix of personal as well as explicitly copied trades; however, these traders are not considered to be trade leaders but rather copiers who reserve a portion of their capital for

[2]Investigating the explicit copying relationship between trade leaders and copiers is also an interesting topic; however, for the purposes of the present study, we only focus on trade leaders who are the ones making the trading decisions.

personal trading. Executing only personal trades signals potential superior status, confidence, and skill, whereby the trade leader is seen by copiers as a unique and autonomous entity with the ability to add value.

The final sample encompasses over 2.6 million transactions executed by 77,476 trade leaders. These transactions can be categorized according to the asset traded as follows: currencies constitute the majority with 83.14% of transactions, whereas commodities, indices, and stocks make up 11.21%, 3.6% and 2.05%, respectively. Moreover, we calculate several trading characteristics, which are first averaged across all transactions for each trade leader, and then averaged across all trade leaders. These statistics are presented in Table 1. On average, 66.11% of transactions are long positions, with a mean leverage ratio of 175. These results are consistent with the idea that trade leaders are considered to be sophisticated, such that they enter in both long and short positions, and are confident enough in their trading abilities to employ high levels of leverage. Regarding the average trade duration, trade leaders keep transactions open for approximately 6 days, which indicates that they are aware of the impact of rollover costs on profits associated with keeping positions open over the weekend. Similarly, the average number of annual trades for trade leaders is around 34, which is much lower than that of the entire sample of participants — the average for the entire sample is 207 —, indicating that trade leaders account for trading costs when optimizing their strategies. Finally, we find that trade leaders trade in around three to four different assets, which suggests that they tend to be specialized in specific assets.

4.2 TradEx Data

The second data set is obtained from a foreign exchange broker, which we call TradEx, and includes more than 6.9 million transactions in 22 currency pairs, executed by 22,545 retail traders between January 2011 and September 2013. TradEx does not offer participants any social trading features, and does not allow the explicit copying of trades, hence we consider all trades to be unique. We calculate several trader characteristics, which are presented in Table

2. On average, 47% of a trader's positions on the TradEx platform are buys, which is around 20% less compared to trade leaders on SocialEx. This suggests that traders on TradEx adopt more short selling strategies. The average trade duration on TradEx is around 1.19 days, which is considerably less than the duration of trades on SocialEx. This suggests that many traders on TradEx are day traders who minimize their exposure to overnight fluctuations in prices. We find that the average number of annual trades is 111, which is almost three times the figure for trade leaders on SocialEx. Given that traders on TradEx are day traders, the higher trade frequency suggests that these individuals seek to exploit intraday price trends. Finally, we find that traders on TradEx trade in an average of 6 different currency pairs. This number is slightly higher than that of trade leaders on SocialEx, and suggests that traders on TradEx have a wider scope when searching for trading opportunities to exploit.

5 Results

In order to test whether the scopic regime governing STPs leads to excess herding, we use the two data sets, SocialEx and TradEx, and estimate herding behavior using the measures presented earlier for quarterly (Q), monthly (M), weekly (W), as well as daily (D) periods.[3]

We recalculate these herding measures for subgroups of these two data sets based on trading intensity, leverage[4], and trade size. Given that the two trading platforms offer different assets and the data sets span over different time periods, we repeat all the analyses on common subsets that are selected by only considering the overlapping time frame and the common assets traded on the two platforms. The results and conclusions we obtain using the common subsets are very similar to those obtained using the full data sets, hence we do not report the results of the common subsets due to space limitations.

[3]Kremer and Nautz (2013) show that the frequency at which the data is observed can have a significant impact on the herding estimates calculated, and subsequently the inferences made about the underlying subjects. Hence, we compute all herding measures using quarterly, monthly, weekly, and daily frequencies.

[4]This analysis is only conducted for the SocialEx data set which allows traders to choose their desired leverage ratio for each trade. The TradEx platform does not allow traders to choose a custom leverage ratio, but instead provides a constant leverage of 200 to 1.

5.1 Overall Herding

For SocialEx, the results presented in Table 3 where $n \geq 0$ (i.e. no restrictions on trade intensity) show that the level of herding among trade leaders ranges between the lower HLSV limits of 19.5%, 18.9%, 16.6%, and 11.8% and the upper HFHW limits of 26.4%, 27.0%, 26.0%, and 21.1% for Q, M, W, and D frequencies, respectively. The IHM also shows evidence of herding with a lower estimate of 1.5% based on a quarterly frequency, and a higher estimate of 3.28% based on a daily frequency. Regarding the Sias measures, we report high and significant $SIAS_{full}$ herding estimates for all frequencies. More importantly, we find that a large portion of herding behavior stems from traders following the previous trades of others, as indicated by the high $SIAS_{other}$ estimates. For example, we report daily $SIAS_{full}$ and $SIAS_{other}$ estimates of 0.775 and 0.759, respectively, indicating that 97.9% of herding is due to traders mimicking others.

The results for TradEx are presented in Table 4. For the full data set (where $n \geq 0$), we report HLSV estimates of 2.5%, 3.3%, 3.4%, and 3.5% and HFHW estimates of 5.0%, 8.0%, 8.7%, and 10.0% for Q, M, W, and D periods, respectively. Regarding the IHM, we report significant herding levels with a lower quarterly estimate of 0.17%, and a higher daily estimate of 0.92%. The results obtained for these three herding measures are significantly lower compared to those obtained for trade leaders on SocialEx, which suggests that the scopic regime encourages herding. With respect to the Sias measures, the estimates obtained for all periods are lower than those obtained for SocialEx. For instance, we report daily $SIAS_{full}$ and $SIAS_{other}$ estimates of 0.361 and 0.335, respectively, which are around half the values reported for SocialEx. Nevertheless, the portion of herding resulting from traders following others (92.8%) is high for traders on TradEx. This may be due to traders adopting common momentum strategies that reflect the previous trading decisions of others.

Our results show significant evidence of a higher overall level of herding among traders under the scopic regime compared to the traditional trading environment. Moreover, the level of herding under the scopic regime is higher compared to the results presented by studies on retail investors in traditional equity markets. Dorn et al. (2008) estimate a mean HLSV of 8.3%, Barber et al. (2009) find herding levels of 6.81% and 12.79% for each of the two data sets they use, and Merli and Roger (2013) conclude that herding among French individual investors falls between the lower HLSV limit of 12.63% and the upper HFHW limit of 21.70%.

The evidence we present clearly indicates that herding behavior among trade leaders on the STP is much higher compared to herding in a traditional trading environment. While part of this herding behavior may be driven by factors that affect traders on both platforms equally, such as common reactions to news announcements, the excess herding can be attributed to the effect of the scopic environment.

5.2 Herding and Trading Intensity

We re-estimate the herding measures using sub-samples of the two data sets that are chosen by applying various thresholds to the minimum number of traders in each security. A higher minimum threshold implies greater trading intensity and liquidity in the sub-sample.

Table 3 shows the results for SocialEx. We find an inverse relationship between herding and the number of traders active in the security, where both the HLSV and HFHW estimates decrease as the number of traders active in a security increases for all frequencies. A similar relation is found for the Sias measures, while the IHM measure shows rather constant herding levels across the thresholds. Our results are similar to the evidence presented by Wermers (1999), and may be explained by the theory of information availability and informational cascades (Bikhchandani et al., 1992; Welch, 1992). Securities with low liquidity are generally not extensively covered by analysts, resulting in scarcity of information. Due to the lack of sufficient information, these securities attract a small number of active traders who may turn to interpreting other traders' transactions as a scarce source of valuable information. By doing so, herding levels in illiquid securities are likely to be higher compared to those where information is more abundant. In order to test this hypothesis, we re-estimate the herding measures at the various thresholds; however, we use a sample containing only the most liquid instruments. This sample includes the major currency pairs: EUR/USD, GBP/USD, NZD/USD, USD/CAD, USD/JPY, USD/CHF, and AUD/USD. The HLSV estimates for all thresholds are constant and equal to 8.9%, 8.5%, 8.1%, and 6.8% for Q, M, W, and D frequencies, respectively, while the HFHW estimates are constant and equal to 12.0%, 13.3%, 12.4%, and 11.2%, for Q, M, W, and D frequencies, respectively. As a consequence, the high herding levels found in less liquid securities can be attributed to lack of sufficient market information.

The results for the TradEx data set are reported in Table 4, and show that the HLSV and HFHW estimates are low and constant for all trading intensity thresholds, and across all frequencies. Regarding the IHM, we also report constant estimates across all thresholds for Q, M, and W frequencies. As for the daily frequency, we report decreasing estimates as trading intensity increases, which is evidence of herding due to informational cascades resulting from the low amount of information that is available during the very short daily time frame. We find that the $SIAS_{full}$ estimates are relatively constant across all thresholds for Q and M periods, and have no or weak significance for W and D periods. However, when we analyze the components of the Sias measure separately, we find statistical significance and constant estimates across all thresholds and frequencies, which is in line with the results of the other measures.

To summarize, herding behavior among trade leaders on SocialEx is higher compared to the results for traders on TradEx for all trading intensities and frequencies. This supports our earlier finding that the scopic environment encourages herding behavior. Moreover, we find that herding in the sub-samples that include assets with low trading intensities (i.e. less liquid assets) is higher only in the SocialEx data set, while this variation is largely lacking in the TradEx data. This suggests that, when trading illiquid assets where information is scarce, traders under the scopic regime try to seek information from the trades of others. Given that order flow is publicly disclosed in a scopic environment, this entices individuals to herd, which can be interpreted as evidence of intentional herding driven by informational cascades.

5.3 Herding and Leverage

The second relationship that we examine is between herding and the degree of leverage used by trade leaders, which is an indication of their risk appetite. This analysis is only conducted on the SocialEx data set since the SocialEx platform allows traders to select their desired leverage ratio, while TradEx imposes a 200 to 1 leverage for all trades. We estimate the herding measures for the different leverage subgroups and present the results in Table 5.

The results for the HLSV, HFHW, and IHM measures show a concave relationship between the degree of leverage and herding. In particular, highly risk-averse traders such as those with leverage ratios of 2 to 1 and 5 to 1 exhibit relatively lower herding levels compared to less risk-averse traders (or medium risk takers with leverage ratios between 10 to 1 and 50 to 1). One possible reason for this result is the scarcity of observations in the lowest leverage subgroups. The last two columns of Table 5, specifically for the leverage ratios 2 to 1 and 5 to 1, show that the number of security-periods and the average number of trades are relatively low compared to the figures shown for other leverage ratios. As a consequence, FHW show using Monte Carlo simulation that, unless the number of trades in a security-period is extremely large, then the HLSV and HFHW measures — as well as the IHM, which is based on the signed HLSV measure — will be biased downward. Another behavioral explanation for this low level of herding is that these trades can be seen as experimental, where trade leaders try out new strategies without taking on too much risk. We could not compute the Sias measures for the 2 to 1 leverage subgroup due to lack of sufficient adjacent observations when estimating Equation (8). As for the 5 to 1 leverage subgroup, we find significant results for the quarterly and monthly frequencies; however the low number of observations renders these results equivocal.

With respect to herding behavior of risk-seeking trade leaders (leverage ratios of 100 to 1, 200 to 1, and 400 to 1), the results show that herding levels are lower than those of their medium-risk counterparts when we examine the HLSV, HFHW, and IHM measures. The results obtained for the Sias measures are mixed, with low frequency periods (Q and M) showing higher herding for risk-seeking traders, while high frequency periods (W and D) showing lower herding. However, the overall relation is that traders with higher leverage ratios tend to herd less. This phenomenon is well documented in the literature by studies such as Scharfstein and Stein (1990) and Gümbel (2005), who find that fund managers who are likely to herd are more risk averse than non-herding managers. The idea is that overconfident traders take on more risk because they tend to underestimate risk and overestimate the conditional expected return from their trading strategies (Odean, 1998; Hirshleifer and Luo, 2001). Analogously, it follows that high risk takers are overconfident in their trading skills and strategies, hence they tend to herd less (De Long et al., 1990, 1991; Hirshleifer and Luo, 2001).

Being risk-prone and overconfident does not necessarily mean that one is more knowledgeable. Highly leveraged trades can be seen as "black swan" trades, which are executed by traders who have a particularly high level of confidence and tolerance for volatility. This can deter other trade leaders from herding, since they would suffer great financial losses and taint their reputation in case the black swan trade goes sour. The safest herding strategy to preserve status as a trade leader would be to stand in the middle of the risk spectrum, and imitate moderately risky trades where a loss will not have a detrimental impact on reputation. In addition, allowing highly leveraged traders to fly solo would work to one's advantage when their trades accrue losses, as this thins out the competition among trade leaders.

5.4 Herding and Trade Size

The third analysis examines the variation in herding depending on trade size. Many studies on hedge funds and mutual funds have shown that as fund managers mature and grow their assets under management, they are more likely to herd because they have more to lose in terms of compensation (Boyson, 2010; Graham, 1999; Scharfstein and Stein, 1990). Following this reasoning, we argue that traders with larger positions are likely to herd more in order to avoid the disappointment of underperforming their peers.

To test this, we first divide the two data sets into quintiles based on trade size, where quintile 1 encompasses the trades with the largest trade sizes while quintile 5 contains the smallest trades, and we estimate the herding measures for each quintile.

The results for SocialEx are presented in Table 6. For quintiles 1 to 4, we show that the quarterly and monthly HLSV and HFHW estimates are higher for larger sized trades. These results are consistent with our argument that the larger a trader's investment, the more he has to lose, and the more he is likely to herd. The estimates for the weekly and daily frequencies show relatively constant herding levels for these quintiles. One explanation for the lack of variation in herding levels across quintiles for the higher frequencies (W and D) is that traders may perform well and increase their wealth and future trade sizes in a short time period, but may take a longer amount of time to fathom the potential disappointment associated with poor performance on large trades. As such, these traders will not exhibit high levels of herding in the short term, as indicated by the W and D results. However, as time passes and these individuals begin to understand the magnitude of losses on large positions, they tend to herd more with their peers. Thus, the Q and M frequencies examine herding within a longer period, where traders have sufficient time to learn about the disappointment of underperformance. The estimates for the Sias measures also show higher herding for the lower frequencies (Q and M), and lower herding for the higher frequencies (W and D), which further supports our argument. The IHM shows opposing but weak results compared to the HLSV and HFHW measures.

With respect to the smallest trade size quintile, herding is estimated to be relatively high for all herding measures. This may be attributed to trade leader sophistication. Our argument draws from the conclusion of Doering et al. (2015) who find significant correlations between social trading returns and almost all the hedge fund trading strategies they consider, indicating that trade leaders may be adopting sophisticated strategies. Hence, we argue that herding behavior for the smallest trade size quintile may be interpreted as follows: a trader invests a small portion of their wealth to buy an option that allows them to mimic the trades of others. Similar to a financial option, the downside risk is limited to the trader's small investment, while there is unlimited upside potential. This option allows the trader to either continue herding and increase their exposure to the other trader if the copied strategy performs well, or to simply cut their losses in case the strategy performs poorly. Nevertheless, further analysis is required in order to understand the relationship between trader sophistication and trade size.

Regarding TradEx, the results reported in Table 7 show that the estimate for all the herding measures are significantly lower compared to the results for SocialEx. The HLSV and HFHW estimates show that traders herd the most when trade size is large, which is consistent with our main argument. The IHM shows relatively constant levels of herding across the trade-size quintiles. With respect to the $SIAS_{full}$ measure, we report in general statistically insignificant results. However, when we analyze the decomposed component $SIAS_{other}$, we find mostly significant estimates that are relatively constant across the quintiles — with the exception of a high quarterly estimate of 68.8% for quintile 5. Nevertheless, the dominating evidence suggests that herding is higher for larger trades.

5.5 Persistence in Herding

We present the contemporaneous and time-series correlations of purchase intensities for SocialEx and TradEx in Table 8 and Table 9, respectively.

For SocialEx, the first row of the table (where $\tau = 0$) shows that the contemporaneous correlations of $\pi_{i,t}$ between G_1 and G_2 are 98.5%, 95.9%, and 77.4% for M, W, and D frequencies, respectively. These figures indicate a very high correlation between the trading decisions of the two random groups of trade leaders in a given period. As explained by Barber et al. (2009), these correlations have an intuitive interpretation, such that the square of the contemporaneous correlation is equivalent to the R^2 obtained from regressing the purchase intensities of G_1 on those of G_2. For example, the R^2 based on a quarterly frequency equals 97.02%, meaning that we can explain almost all the variation in the purchase intensities of one group of trade leaders by knowing the purchase intensities of another group. As for traders on TradEx, we report contemporaneous correlations (where $\tau = 0$) of 58.4%, 48.2%, and 32.7% for M, W, and D frequencies, respectively. These results are significantly lower compared to those of trade leaders, thus confirming our earlier results of higher herding levels under the scopic regime relative to a traditional trading environment. Furthermore, compared to the evidence presented in the literature on individual equity investors, the monthly contemporaneous correlation among trade leaders on SocialEx is around 14% and 24% higher than the results reported by Merli and Roger (2013) and Barber et al. (2009), respectively.

The remaining rows of Table 8 and Table 9 (i.e. where $\tau > 0$) show the correlations between the purchase intensities at time t and $t + \tau$ for SocialEx and TradEx, respectively. In general, the correlations for trade leaders on SocialEx are significantly higher compared to those of traders on TradEx across all time horizons, and for all frequencies. For example, given a time horizon of $\tau = 1$, we report correlations for SocialEx greater than 90% for M and W frequencies and greater than 70% for a daily frequency. The results for TradEx given the same τ are around 39%, 33%, and 22% for M, W, and D frequencies, respectively. Moreover, the results reported in the literature for individual equity investors based on a monthly frequency for the same time horizon of $\tau = 1$ are similar to those of traders on TradEx. For instance, Merli and Roger (2013) report correlations of 30.27% and 31.50%, and Barber et al. (2009) report values between 46.7% and 48.2% for the large discount broker and 55.8% and 58.6% for the large retail broker. Similar results are found for the rest of the time horizons, indicating that persistence in herding behavior is significantly higher under a scopic regime compared to a traditional trading environment.

Another important finding of this analysis is that persistence fades away at a slower rate under a scopic environment compared to a traditional trading environment. For example, based on a monthly frequency and considering the two time horizons $\tau = 6$ and $\tau = 11$, the correlations for trade leaders on SocialEx are around 80% and 70%, respectively — down from around 92% for $\tau = 1$. The correlations for the same time horizons on TradEx are around 24% — down from around 39% for $\tau = 1$. Similarly for individual equity investors, Barber et al. (2009) report correlations of 17.9% and 10.3% for the same time horizons at the large discount broker, and 31.8% and 23.2% at the large retail broker, while Merli and Roger (2013) report correlations of 8.21% and 3.55% for the two time horizons, respectively.

The strong evidence of persistence in herding over the various time horizons under the scopic regime indicates that this phenomenon is not due to momentary events of increased uncertainty. Herding remains relatively high even across a horizon of almost one year. The significant difference in the rate of decay of persistence in herding over time between trade leaders in a scopic environment and traders in a traditional trading environment indicates that social trading, through its social features and scopic regime, has an additional conformism effect on participants. Trade leaders do not imitate each other only in the current period, but rather do so continuously across long time lags, which is made possible given the publicly disclosed order flow data on the STP. This finding challenges traditional financial theory since it shows that individuals under a scopic environment look at past information and trading activity as far back as one year when making trading decisions. One explanation for this phenomenon is that the excess herding produced by the scopic environment is stimulated by the limitations and biases of individual traders to analyze a large number of assets in a highly dynamic environment. Hence, these individuals may simply opt to imitate the consensus of the majority even across long time lags. While this persistence can be considered as intentional perpetual herding, further research is necessary to investigate whether order flow data may still contain genuine predictive power, despite it being publicly disclosed on the platform. Such an analysis would allow us to determine whether the autoregressive pattern in herding behavior is rational.

6 Conclusion

Does a scopic, information-rich environment augment the limitations and personal biases of individual traders, thus producing excess and perpetual herding levels that are higher than those found in traditional trading environments? Using data from a popular STP, which we call SocialEx, that is governed by a scopic regime and mandates high information transparency regarding order flow, and another data set from an anonymous online foreign exchange broker, we show that the scopic environment produces excess levels of herding over and above those found in traditional trading environments. Moreover, we show that herding among trade leaders on the STP is high when market information is scarce, and that this heightened level of herding is absent among traders on TradEx. This indicates that the scopic environment encourages individuals to seek information from the activities of others when market information regarding an asset is limited, which may be interpreted as evidence of intentional herding due to informational cascades. We find herding to be relatively low among risk-seeking trade leaders, which supports the notion that risk-seekers tend to be overconfident in their own abilities, thus herd less. In addition, high-risk strategies tend to deter others from following suit. As such, the scopic regime encourages herding mostly in the middle of the risk spectrum, where traders understand that there is a modest trade-off between maintaining status quo as leaders and avoiding large losses. Our results also show that traders who have more to lose are more likely to herd as they fathom the disappointment associated with underperforming on large positions. Moreover, herding is high for the smallest sized trades in the scopic environment, which may be due to trade leaders using very small portions of their capital as an option to try and emulate potentially profitable trades. Finally, we show that herding in the scopic environment persists across several time horizons at much higher levels, and fades away much slower compared to herding in traditional environments.

Our findings challenge traditional financial theory since we show that exposure to more information leads to increased local levels of and persistence in herding behavior. This means that trade leaders base their trading decisions in large part on the current and historical trading activities of others. We argue that the scopic environment augments the biases and limited capacity of individual retail traders to analyze many assets and make quick decisions in a highly dynamic environment, consequently prompting traders to imitate the actions of others irrespective of how dated they are. Hence, the information-rich scopic environment stimulates a conformist attitude towards trading, whereby individuals easily mimic the trading activities of others. The motivation to adopt this attitude is further boosted by the compensation schemes offered to traders who manage the capital of copiers. As a consequence, traders choose to herd continuously in order to avoid underperforming their peers and tarnishing their reputation. While our findings suggest that the excess and perpetual herding generated by the scopic environment is intentional, further research on the information content of publicly disclosed order flow data is necessary to investigate whether this behavior is rational. The data limitations in this paper do not allow us to investigate herding in relation to trader performance and demographics. Hence, future research can provide refined insight into whether trade leaders are more likely to herd with those who have performed well in the past, or those who belong to a specific demographic group. For instance, researchers can investigate whether traders who herd in a scopic environment exhibit the hot hand fallacy, whereby they expect past performance of experts to be positively correlated with future performance in a market that is typically characterized by a random walk (Huber et al., 2010). Such an analysis could show whether individuals tend to herd with those who they deem to be informed, and whether mimicking their future trades would generate superior risk-adjusted returns.

The high level of and persistence in herding behavior among trade leaders on STPs unveils several implications. First, from a macroeconomic perspective, it has been argued that intentional herding increases market volatility due to the high correlation among trades (Hirshleifer and Hong Teoh, 2003; Barber et al., 2009). This issue may quickly materialize as STPs become more popular among retail traders, while regulators remain largely absent from monitoring these platforms and setting pre-emptive protocols to protect naïve investors. Second, with respect to copiers who wish to diversify across multiple trade leaders, the benefits of diversification are greatly diminished in the presence of herding. This is because trade leaders who herd are essentially trading the same assets in the same direction and at the same time. Hence, copiers should proceed with caution and take into account herding behavior when selecting the trade leaders they wish to allocate their funds to. Third, STPs offer performance compensation programs to trade leaders based on the number of copiers they attract or on their actual trading performance. While trade leaders who are authentically skilled should be compensated for their efforts and added value, others who simply herd should not be compensated similarly, since this may drive truly skilled traders to exit the social trading network. Finally, while our study focuses on retail traders who are predominantly active in the foreign exchange market, our findings can be extrapolated to other financial markets as well as institutional traders, such as hedge funds, who are under constant pressure to disclose their holdings and strategies so that investors have greater transparency regarding their investments. Investors may enjoy having a clearer picture of how their money is invested; however, this comes at the cost of increased herding among hedge funds, curtailed authentic research and lower potential returns.

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Table 1: **Descriptive Statistics of Trades Executed by Trade Leaders During 2013 on SocialEx.** The following table shows descriptive statistics of all trades executed by trade leaders during 2013 on SocialEx. The **Financial Instruments** subgroups show the proportion of all trades where the underlying asset is a currency, commodity, index, or stock, respectively. The table also presents several trading behavior attributes. **Long** represents the average proportion of trades that are long positions. **Leverage** is the average leverage ratio employed by a trader. **Time** is the average duration of a trade measured in days. **Annual Trades** and **Weekly Trades** are the number of annual and average weekly trades, respectively, per trader. **Instruments** is the number of different financial instruments traded by a trader.

Number of Trades	=	2,640,972				
Number of Users	=	77,476				
Trade Close Type				**Financial Instruments**		
Manual	=	62.76%		*Currencies*	=	83.14%
Stop Loss	=	22.04%		*Commodities*	=	11.21%
Take Profit	=	13.14%		*Indicies*	=	3.60%
Rollover	=	2.06%		*Stocks*	=	2.05%
	Long	**Leverage**	**Time (days)**	**Annual Trades**	**Weekly Trades**	**Instruments**
Mean	66.11%	175	6.08	34.18	1	3.61
Min	0.0%	1.0	0.01	1	0.02	1
Max	100%	400.0	347	14,672	282	71
St.Dev.	0.355	156.51	17.24	166.32	3.20	4.36

Table 2: **Descriptive Statistics of Trades Executed by Traders on TradEx During From January 2011 to September 2013.** The following table shows descriptive statistics of all trades executed by traders from January 2011 to September 2013. The table presents several trading behavior attributes. **Long** represents the average proportion of trades that are long positions. **Leverage** is the average leverage ratio employed by a trader. **Time** is the average duration of a trade measured in days. **Annual Trades** and **Weekly Trades** are the number of annual and average weekly trades, respectively, per trader. **Instruments** is the number of different financial instruments traded by a trader.

Number of Trades	=	6,928,399
Number of Traders	=	22,545
Trade Close Type		
Manual	=	66.48%
Stop Loss	=	14.41%
Take Profit	=	19.11%

	Long	**Leverage**	**Time (days)**	**Annual Trades**	**Weekly Trades**	**Instruments**
Mean	47.00%	200	1.19	111.75	2.15	5.72
Min	0.0%	200	0.01	1	0.02	1
Max	100%	200	229.1	31,765	610.87	22
St.Dev.	0.164	0	3.39	382.02	7.35	4.65

Table 3: **Herding and Trading Intensity on SocialEx.** This table presents the estimated coefficients of the herding measures $HLSV$, $HFHW$, IHM, $SIAS_{full}$, $SIAS_{own}$, and $SIAS_{other}$ for the SocialEx data set based on several minimum thresholds for the number of transactions executed. Standard errors for each herding measure are shown in parentheses underneath the estimates. Herding measures are reported for quarterly (Q), monthly (M), weekly (W), and daily (D) periods. Moreover, the number of instrument-periods, (i, t) and average number of trades per instrument, $Trades$ are also reported.

Min. Trades	t	$HLSV$		$HFHW$		IHM		$SIAS_{full}$		$SIAS_{own}$		$SIAS_{other}$		(i,t)	$Trades$
$n \geq 0$	Q	0.195	***	0.264	***	0.015	***	0.865	***	0.003		0.862	***	311	12,977
		(0.02)		(0.009)		(0.0002)		(0.05)		(0.002)		(0.02)			
	M	0.189	***	0.270	***	0.0184	***	0.918	***	0.01	***	0.907	***	795	4,622
		(0.01)		(0.006)		(0.0002)		(0.05)		(0.003)		(0.02)			
	W	0.166	***	0.260	***	0.0237	***	0.924	***	0.025	***	0.899	***	2,426	1,280
		(0.006)		(0.003)		(0.0003)		(0.06)		(0.004)		(0.01)			
	D	0.118	***	0.211	***	0.0328	***	0.775	***	0.016	***	0.759	***	8,895	290
		(0.002)		(0.001)		(0.0004)		(0.133)		(0.001)		(0.01)			
$n \geq 100$	Q	0.172	***	0.230	***	0.021	***	0.850	***	0.001	***	0.849	***	166	17,881
		(0.02)		(0.007)		(0.0004)		(0.08)		$(3.7e^{-5})$		(0.06)			
	M	0.142	***	0.195	***	0.0259	***	0.782	***	0.002	***	0.780	***	360	7,510
		(0.012)		(0.005)		(0.0005)		(0.108)		(0.0001)		(0.05)			
	W	0.126	***	0.184	***	0.034	***	0.850	***	0.004	***	0.846	***	1,339	1,956
		(0.004)		(0.002)		(0.0007)		(0.105)		(0.0001)		(0.02)			
	D	0.107	***	0.171	***	0.0405	***	0.822	***	0.004	***	0.818	***	4,406	510
		(0.002)		(0.001)		(0.0008)		(0.158)		(0.0001)		(0.01)			
$n \geq 200$	Q	0.147	***	0.199	***	0.0214	***	0.788	***	0.0004	***	0.787	***	132	21,100
		(0.02)		(0.008)		(0.0004)		(0.101)		$(4.6e^{-5})$		(0.137)			
	M	0.134	***	0.184	***	0.0264	***	0.778	***	0.001	***	0.777	***	332	7,964
		(0.01)		(0.004)		(0.0005)		(0.111)		(0.0001)		(0.04)			
	W	0.127	***	0.181	***	0.0348	***	0.857	***	0.003	***	0.854	***	1,198	2,162
		(0.004)		(0.002)		(0.0007)		(0.109)		(0.0001)		(0.02)			
	D	0.09	***	0.150	***	0.041	***	0.827	***	0.003	***	0.824	***	2,910	709
		(0.003)		(0.001)		(0.0009)		(0.183)		(0.0001)		(0.02)			
$n \geq 300$	Q	0.142	***	0.193	***	0.0206	***	0.792	***	0.0005	***	0.791	***	124	21,917
		(0.02)		(0.007)		(0.0004)		(0.104)		$(4.8e^{-5})$		(0.138)			
	M	0.131	***	0.180	***	0.0258	***	0.778	***	0.001	***	0.778	***	318	8,279
		(0.01)		(0.003)		(0.0005)		(0.114)		$(4.9e^{-5})$		(0.04)			
	W	0.129	***	0.181	***	0.0342	***	0.863	***	0.002	***	0.860	***	1,068	2,394
		(0.004)		(0.002)		(0.0007)		(0.112)		(0.0001)		(0.02)			
	D	0.08	***	0.139	***	0.0406	***	0.823	***	0.0025	***	0.820	***	2,180	896
		(0.003)		(0.001)		(0.0009)		(0.219)		$(4.6e^{-5})$		(0.02)			
$n \geq 400$	Q	0.134	***	0.182	***	0.0199	***	0.796	***	0.0005	***	0.795	***	115	23,185
		(0.02)		(0.008)		(0.0004)		(0.120)		(0.0001)		(0.139)			
	M	0.131	***	0.180	***	0.0251	***	0.785	***	0.001	***	0.784	***	313	8,375
		(0.01)		(0.004)		(0.0005)		(0.112)		(0.0001)		(0.05)			
	W	0.132	***	0.183	***	0.034	***	0.869	***	0.002	***	0.866	***	980	2,582
		(0.004)		(0.002)		(0.0007)		(0.117)		(0.0001)		(0.02)			
	D	0.08	***	0.135	***	0.0405	***	0.799	***	0.0025	***	0.797	***	1,708	1,100
		(0.003)		(0.001)		(0.0009)		(0.241)		(0.0001)		(0.03)			
$n \geq 500$	Q	0.130	***	0.177	***	0.0206	***	0.795	***	0.0005	***	0.794	***	111	23,743
		(0.02)		(0.006)		(0.0004)		(0.119)		$(4.1e^{-5})$		(0.139)			
	M	0.130	***	0.179	***	0.0255	***	0.783	***	0.001	***	0.781	***	309	8,462
		(0.011)		(0.004)		(0.0005)		(0.113)		(0.0001)		(0.05)			
	W	0.132	***	0.182	***	0.0344	***	0.859	***	0.002	***	0.857	***	871	2,856
		(0.005)		(0.002)		(0.0007)		(0.127)		(0.0001)		(0.02)			
	D	0.079	***	0.127	***	0.0409	***	0.796	***	0.002	***	0.794	***	1,411	1,241
		(0.002)		(0.001)		(0.0009)		(0.275)		(0.0001)		(0.05)			

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4: **Herding and Trading Intensity on TradEx.** This table presents the estimated coefficients of the herding measures $HLSV$, $HFHW$, IHM, $SIAS_{full}$, $SIAS_{own}$, and $SIAS_{other}$ for the TradEx data set based on several minimum thresholds for the number of transactions executed. Standard errors for each herding measure are shown in parentheses underneath the estimates. Herding measures are reported for quarterly (Q), monthly (M), weekly (W), and daily (D) periods. Moreover, the number of instrument-periods, (i, t) and average number of trades per instrument, $Trades$ are also reported.

Min. Trades	t	$HLSV$		$HFHW$		IHM		$SIAS_{full}$		$SIAS_{own}$		$SIAS_{other}$		(i,t)	$Trades$
$n \geq 0$	Q	0.025	***	0.05	***	0.0017	***	0.672	***	0.002	**	0.670	***	188	35,606
		(0.008)		(0.002)		(0.0001)		(0.22)		(0.001)		(0.08)			
	M	0.033	***	0.08	***	0.0024	***	0.494	**	0.004	***	0.489	***	510	12,950
		(0.005)		(0.003)		(0.0001)		(0.216)		(0.001)		(0.06)			
	W	0.034	***	0.087	***	0.0044	***	0.429	*	0.011	***	0.418	***	2,094	3,193
		(0.002)		(0.001)		(0.0001)		(0.229)		(0.001)		(0.031)			
	D	0.035	***	0.10	***	0.0092	***	0.361		0.026	***	0.335	***	10,395	607
		(0.001)		(0.0005)		(0.0002)		(0.274)		(0.001)		(0.014)			
$n \geq 100$	Q	0.022	***	0.045	***	0.0017	***	0.661	***	0.001	***	0.660	***	174	35,657
		(0.008)		(0.001)		(0.0001)		(0.239)		(0.0001)		(0.08)			
	M	0.029	***	0.068	***	0.0024	***	0.504	**	0.003	***	0.501	***	478	13,073
		(0.004)		(0.001)		(0.0001)		(0.228)		(0.0002)		(0.06)			
	W	0.034	***	0.077	***	0.0043	***	0.437		0.006	***	0.431	***	1,758	3,530
		(0.002)		(0.0004)		(0.0001)		(0.268)		(0.0002)		(0.03)			
	D	0.029	***	0.073	***	0.0085	***	0.376		0.006	***	0.370	***	5,268	1,067
		(0.001)		(0.0003)		(0.0002)		(0.338)		(0.0002)		(0.023)			
$n \geq 200$	Q	0.023	***	0.051	***	0.0016	***	0.677	***	0.001	***	0.676	***	167	35,792
		(0.006)		(0.001)		(0.0001)		(0.244)		(0.0001)		(0.09)			
	M	0.03	***	0.065	***	0.0024	***	0.539	**	0.0024	***	0.537	***	445	13,922
		(0.003)		(0.001)		(0.0001)		(0.232)		(0.0002)		(0.07)			
	W	0.032	***	0.069	***	0.0042	***	0.423		0.005	***	0.418	***	1,515	4,033
		(0.002)		(0.0004)		(0.0001)		(0.289)		(0.0002)		(0.037)			
	D	0.023	***	0.058	***	0.0075	***	0.397		0.0031	***	0.394	***	3,704	1,507
		(0.001)		(0.0002)		(0.0001)		(0.347)		(0.0001)		(0.029)			
$n \geq 300$	Q	0.024	***	0.051	***	0.0016	***	0.665	***	0.001	***	0.664	***	163	36,054
		(0.006)		(0.001)		(0.0001)		(0.253)		(0.0001)		(0.08)			
	M	0.03	***	0.063	***	0.0024	***	0.499	**	0.002	***	0.496	***	430	14,186
		(0.003)		(0.001)		(0.0001)		(0.243)		(0.0001)		(0.07)			
	W	0.031	***	0.065	***	0.0042	***	0.486		0.004	***	0.482	***	1,323	4,546
		(0.002)		(0.0003)		(0.0001)		(0.309)		(0.0002)		(0.038)			
	D	0.022	***	0.054	***	0.0066	***	0.372		0.0025	***	0.369	***	2,963	1,867
		(0.001)		(0.0001)		(0.0001)		(0.340)		(0.0001)		(0.036)			
$n \geq 400$	Q	0.023	***	0.051	***	0.0016	***	0.684	***	0.001	***	0.684	***	158	36,421
		(0.006)		(0.001)		(0.0001)		(0.261)		(0.0001)		(0.08)			
	M	0.029	***	0.061	***	0.0024	***	0.508	**	0.0022	***	0.506	***	416	14,452
		(0.003)		(0.001)		(0.0001)		(0.253)		(0.0001)		(0.07)			
	W	0.032	***	0.064	***	0.0042	***	0.524	*	0.003	***	0.521	***	1,176	5,079
		(0.002)		(0.0003)		(0.0001)		(0.311)		(0.0001)		(0.046)			
	D	0.021	***	0.049	***	0.0064	***	0.396		0.002	***	0.394	***	2,450	2,210
		(0.001)		(0.0001)		(0.0001)		(0.389)		(0.0001)		(0.04)			
$n \geq 500$	Q	0.024	***	0.052	***	0.0016	***	0.758	***	0.001	***	0.757	***	154	36,717
		(0.006)		(0.001)		(0.0001)		(0.232)		(0.0001)		(0.08)			
	M	0.029	***	0.059	***	0.0024	***	0.539	**	0.002	***	0.537	***	398	14,938
		(0.003)		(0.0004)		(0.0001)		(0.247)		(0.0001)		(0.06)			
	W	0.032	***	0.063	***	0.0041	***	0.509		0.0026	***	0.506	***	1,045	5,657
		(0.002)		(0.0003)		(0.0001)		(0.317)		(0.0001)		(0.048)			
	D	0.02	***	0.046	***	0.0061	***	0.468		0.002	***	0.467	***	2,022	2,671
		(0.001)		(0.001)		(0.0001)		(0.425)		(0.0001)		(0.047)			

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 5: **Herding and Leverage on SocialEx.** This table presents the estimated coefficients of the herding measures $HLSV$, $HFHW$, IHM, $SIAS_{full}$, $SIAS_{own}$, and $SIAS_{other}$ for the SocialEx data set based on the different levels of leverage used. Standard errors for each herding measure are shown in parentheses underneath the estimates. Herding measures are reported for quarterly (Q), monthly (M), weekly (W), and daily (D) periods. Moreover, the number of instrument-periods, (i, t) and average number of trades per instrument, $Trades$ are also reported.

Leverage	t	$HLSV$	$HFHW$	IHM	$SIAS_{full}$	$SIAS_{own}$	$SIAS_{other}$	(i,t)	$Trades$
2 to 1	Q	0.075 ***	0.280 ***	0.0395 ***	NA	NA	NA	37	13
		(0.019)	(0.035)	(0.0117)					
	M	0.045 **	0.234 ***	0.0262 *	NA	NA	NA	59	7
		(0.018)	(0.027)	(0.014)					
	W	0.0031	0.201	0.0369 **	NA	NA	NA	96	3
		(0.0023)	(0.132)	(0.0146)					
	D	0.012 *	0.113 *	0.0363 ***	NA	NA	NA	110	<1
		(0.0067)	(0.065)	(0.0131)					
5 to 1	Q	0.095 ***	0.238 ***	0.0259 ***	0.546 **	0.106	0.440 ***	54	34
		(0.022)	(0.021)	(0.0053)	(0.216)	(0.093)	(0.066)		
	M	0.091 ***	0.283 ***	0.0443 ***	0.354	0.045 ***	0.309 ***	77	16
		(0.012)	(0.016)	(0.0068)	(0.377)	(0.013)	(0.062)		
	W	0.056 ***	0.158 ***	0.0611 ***	NA	NA	NA	108	11
		(0.012)	(0.008)	(0.0081)					
	D	0.0956 ***	0.128 ***	0.0664 ***	NA	NA	NA	25	8
		(0.0049)	(0.006)	(0.0099)					
10 to 1	Q	0.125 ***	0.238 ***	0.0323 ***	0.644 ***	0.017 ***	0.627 ***	100	265
		(0.014)	(0.010)	(0.0028)	(0.147)	(0.003)	(0.059)		
	M	0.110 ***	0.256 ***	0.0373 ***	0.654 ***	0.044 ***	0.610 ***	286	92
		(0.011)	(0.012)	(0.0029)	(0.184)	(0.007)	(0.049)		
	W	0.094 ***	0.222 ***	0.0575 ***	0.600 **	0.242	0.358 ***	680	35
		(0.0068)	(0.005)	(0.0034)	(0.250)	(0.197)	(0.047)		
	D	0.061 ***	0.173 ***	0.0784 ***	0.518	0.419 ***	0.099	1,116	14
		(0.004)	(0.002)	(0.004)	(0.395)	(0.072)	(0.102)		
25 to 1	Q	0.143 ***	0.210 ***	0.0492 ***	0.793 ***	0.002	0.791 ***	105	1,742
		(0.007)	(0.004)	(0.0017)	(0.001)	(0.071)	(0.134)		
	M	0.133 ***	0.215 ***	0.0589 ***	0.493 ***	0.011 ***	0.482 ***	310	591
		(0.007)	(0.003)	(0.0019)	(0.172)	(0.0016)	(0.069)		
	W	0.105 ***	0.203 ***	0.0769 ***	0.583 ***	0.038 ***	0.545 ***	1,248	145
		(0.004)	(0.002)	(0.0022)	(0.176)	(0.002)	(0.027)		
	D	0.096 ***	0.215 ***	0.097 ***	0.562 **	0.083 ***	0.479 ***	4,308	36
		(0.003)	(0.001)	(0.0025)	(0.236)	(0.004)	(0.016)		
50 to 1	Q	0.124 ***	0.173 ***	0.0444 ***	0.709 ***	0.001 ***	0.708 ***	105	4,294
		(0.011)	(0.003)	(0.0009)	(0.130)	(0.0002)	(0.213)		
	M	0.121 ***	0.180 ***	0.0535 ***	0.602 ***	0.005 ***	0.597 ***	310	1,463
		(0.007)	(0.002)	(0.0009)	(0.147)	(0.0007)	(0.068)		
	W	0.108 ***	0.183 ***	0.0648 ***	0.574 ***	0.0179 ***	0.556 ***	1,300	347
		(0.004)	(0.001)	(0.0009)	(0.163)	(0.002)	(0.033)		
	D	0.091 ***	0.192 ***	0.0814 ***	0.475 **	0.039 ***	0.435 ***	5,931	68
		(0.002)	(0.001)	(0.0011)	(0.206)	(0.002)	(0.016)		
100 to 1	Q	0.101 ***	0.142 ***	0.0189 ***	0.725 ***	0.0006 ***	0.724 ***	105	9,360
		(0.011)	(0.003)	(0.0004)	(0.139)	$(3.4e^{-5})$	(0.144)		
	M	0.105 ***	0.151 ***	0.0241 ***	0.607 ***	0.002 **	0.605 ***	310	3,161
		(0.004)	(0.001)	(0.0004)	(0.141)	(0.001)	(0.08)		
	W	0.0952 ***	0.155 ***	0.0306 ***	0.563 ***	0.0077 ***	0.556 ***	1,326	736
		(0.003)	(0.001)	(0.0005)	(0.164)	(0.0004)	(0.037)		
	D	0.078 ***	0.163 ***	0.0416 ***	0.375 *	0.021 ***	0.354 ***	7,091	129
		(0.001)	(0.001)	(0.0006)	(0.194)	(0.001)	(0.017)		
200 to 1	Q	0.082 ***	0.130 ***	0.0122 ***	0.823 ***	0.0005 ***	0.822 ***	65	3,680
		(0.012)	(0.004)	(0.0004)	(0.176)	$(3.9e^{-5})$	(0.240)		
	M	0.084 ***	0.142 ***	0.0148 ***	0.631 ***	0.002 ***	0.629 ***	194	1,233
		(0.007)	(0.002)	(0.0004)	(0.202)	(0.0002)	(0.08)		
	W	0.07 ***	0.143 ***	0.0179 ***	0.409 *	0.007 ***	0.402 ***	838	285
		(0.004)	(0.001)	(0.0005)	(0.235)	(0.0004)	(0.038)		
	D	0.048 ***	0.139 ***	0.0245 ***	0.427	0.027 ***	0.399 ***	3,790	58
		(0.002)	(0.001)	(0.0005)	(0.265)	(0.001)	(0.022)		
400 to 1	Q	0.080 ***	0.125 ***	0.0065 ***	0.887 ***	0.0003 ***	0.887 ***	61	11,427
		(0.011)	(0.003)	(0.0002)	(0.171)	$(3.4e^{-5})$	(0.139)		
	M	0.087 ***	0.133 ***	0.0086 ***	0.682 ***	0.001 ***	0.681 ***	182	3,831
		(0.006)	(0.002)	(0.0002)	(0.181)	(0.0003)	(0.071)		
	W	0.071 ***	0.130 ***	0.0111 ***	0.520 **	0.005 ***	0.515 ***	786	887
		(0.003)	(0.001)	(0.0003)	(0.223)	(0.0002)	(0.044)		
	D	0.054 ***	0.137 ***	0.0157 ***	0.315	0.0197 ***	0.295 ***	4,180	157
		(0.002)	(0.001)	(0.0003)	(0.259)	(0.001)	(0.023)		

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6: **Herding and Trade Size on SocialEx.** This table presents the estimated coefficients of the herding measures $HLSV$, $HFHW$, IHM, $SIAS_{full}$, $SIAS_{own}$, and $SIAS_{other}$ for the SocialEx data set based on trade size that is allocated into quintiles. Quintile 1 contains the largest trades while quintile 5 contains the smallest trades. Standard errors for each herding measure are shown in parentheses underneath the estimates. Herding measures are reported for quarterly (Q), monthly (M), weekly (W), and daily (D) periods. Moreover, the number of instrument-periods, (i,t) and average number of trades per instrument, $Trades$ are also reported.

Quintile	t	$HLSV$		$HFHW$		IHM		$SIAS_{full}$		$SIAS_{own}$		$SIAS_{other}$		(i,t)	$Trades$
1 (Largest)	Q	0.188	***	0.318	***	0.0139	***	0.915	***	0.013	***	0.902	***	246	2,613
		(0.024)		(0.024)		(0.0007)		(0.074)		(0.003)		(0.047)			
	M	0.168	***	0.303	***	0.0184	***	0.809	***	0.055	***	0.755	***	569	991
		(0.013)		(0.013)		(0.0009)		(0.101)		(0.011)		(0.042)			
	W	0.118	***	0.215	***	0.0256	***	0.504	***	0.06	***	0.443	***	1,453	339
		(0.005)		(0.003)		(0.0015)		(0.165)		(0.009)		(0.03)			
	D	0.083	***	0.188	***	0.0293	***	0.457	*	0.054	***	0.403	***	6,375	76
		(0.002)		(0.001)		(0.0018)		(0.25)		(0.003)		(0.018)			
2	Q	0.166	***	0.260	***	0.0118	***	0.895	***	0.004	**	0.891	***	284	2,171
		(0.017)		(0.017)		(0.0005)		(0.057)		(0.002)		(0.042)			
	M	0.161	***	0.272	***	0.0164	***	0.841	***	0.019	**	0.821	***	653	811
		(0.010)		(0.009)		(0.0007)		(0.087)		(0.008)		(0.034)			
	W	0.132	***	0.230	***	0.0224	***	0.579	***	0.024	***	0.555	***	1,514	294
		(0.005)		(0.003)		(0.001)		(0.159)		(0.004)		(0.032)			
	D	0.089	***	0.193	***	0.0279	***	0.476	*	0.021	***	0.456	***	6,322	77
		(0.002)		(0.001)		(0.0012)		(0.243)		(0.002)		(0.017)			
3	Q	0.154	***	0.255	***	0.0244	***	0.838	***	0.006		0.832	***	255	2,821
		(0.021)		(0.018)		(0.0086)		(0.074)		(0.004)		(0.092)			
	M	0.139	***	0.242	***	0.0289	***	0.820	***	0.016	*	0.804	***	585	1,041
		(0.009)		(0.009)		(0.0007)		(0.105)		(0.009)		(0.046)			
	W	0.120	***	0.211	***	0.0366	***	0.559	***	0.02	***	0.539	***	1,272	324
		(0.005)		(0.003)		(0.0009)		(0.173)		(0.006)		(0.038)			
	D	0.088	***	0.189	***	0.0424	***	0.453	*	0.015	***	0.438	***	5,891	81
		(0.002)		(0.001)		(0.0011)		(0.251)		(0.001)		(0.017)			
4	Q	0.123	***	0.180	***	0.0177	***	0.807	***	0.002		0.805	***	267	3,377
		(0.011)		(0.007)		(0.0007)		(0.081)		(0.002)		(0.110)			
	M	0.117	***	0.185	***	0.0246	***	0.880	***	0.007	**	0.873	***	666	1,231
		(0.007)		(0.005)		(0.0009)		(0.082)		(0.003)		(0.027)			
	W	0.130	***	0.213	***	0.034	***	0.756	***	0.018	***	0.739	***	1,472	408
		(0.006)		(0.003)		(0.0013)		(0.134)		(0.004)		(0.033)			
	D	0.086	***	0.188	***	0.0416	***	0.46	*	0.013	***	0.447	***	5,548	82
		(0.003)		(0.001)		(0.0016)		(0.266)		(0.001)		(0.019)			
5 (Smallest)	Q	0.169	***	0.269	***	0.0318	***	0.816	***	0.006	**	0.810	***	266	5,906
		(0.030)		(0.019)		(0.0006)		(0.068)		(0.003)		(0.110)			
	M	0.150	***	0.254	***	0.039	***	0.913	***	0.009	***	0.904	***	649	2,095
		(0.013)		(0.010)		(0.0008)		(0.065)		(0.003)		(0.022)			
	W	0.122	***	0.222	***	0.0497	***	0.857	***	0.016	***	0.841	***	1,271	656
		(0.007)		(0.005)		(0.001)		(0.115)		(0.004)		(0.016)			
	D	0.063	***	0.159	***	0.0585	***	0.392		0.017	***	0.376	***	5,090	94
		(0.002)		(0.001)		(0.0012)		(0.294)		(0.001)		(0.024)			

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 7: **Herding and Trade Size on TradEx.** This table presents the estimated coefficients of the herding measures $HLSV$, $HFHW$, IHM, $SIAS_{full}$, $SIAS_{own}$, and $SIAS_{other}$ for the TradEx data set based on trade size that is allocated into quintiles. Quintile 1 contains the largest trades while quintile 5 contains the smallest trades. Standard errors for each herding measure are shown in parentheses underneath the estimates. Herding measures are reported for quarterly (Q), monthly (M), weekly (W), and daily (D) periods. Moreover, the number of instrument-periods, (i,t) and average number of trades per instrument, $Trades$ are also reported.

Quintile	t	$HLSV$		$HFHW$		IHM		$SIAS_{full}$		$SIAS_{own}$		$SIAS_{other}$		(i,t)	$Trades$
1 (Largest)	Q	0.024	***	0.068	***	0.0039	***	0.371		0.003	***	0.369	***	177	6,480
		(0.005)		(0.001)		(0.0004)		(0.292)		(0.0003)		(0.137)			
	M	0.025	***	0.075	***	0.0059	***	0.196		0.011	***	0.184	***	482	2,367
		(0.004)		(0.001)		(0.0005)		(0.274)		(0.002)		(0.058)			
	W	0.03	***	0.101	***	0.0091	***	0.309		0.051	***	0.259	***	1,769	649
		(0.0025)		(0.001)		(0.0007)		(0.261)		(0.007)		(0.042)			
	D	0.025	***	0.105	***	0.0131	***	0.407		0.081	***	0.326	***	6,469	167
		(0.001)		(0.001)		(0.0008)		(0.365)		(0.004)		(0.024)			
2	Q	0.015	*	0.036	***	0.004	***	0.145		0.002	***	0.143		178	7,264
		(0.008)		(0.003)		(0.0003)		(0.266)		(0.0004)		(0.207)			
	M	0.019	***	0.062	***	0.0062	***	0.197		0.006	***	0.191	**	486	2,717
		(0.004)		(0.001)		(0.0004)		(0.273)		(0.0007)		(0.089)			
	W	0.02	***	0.073	***	0.0095	***	0.307		0.019	***	0.287	***	1,852	706
		(0.002)		(0.001)		(0.0006)		(0.258)		(0.001)		(0.04)			
	D	0.02	***	0.088	***	0.0139	***	0.398		0.054	***	0.344	***	7,204	163
		(0.001)		(0.001)		(0.0007)		(0.361)		(0.003)		(0.024)			
3	Q	0.0276	***	0.072	***	0.0041	***	0.182		0.001		0.180		108	10,591
		(0.003)		(0.002)		(0.0003)		(0.424)		(0.001)		(0.232)			
	M	0.024	***	0.064	***	0.0059	***	0.08		0.004	***	0.076		268	3,979
		(0.003)		(0.001)		(0.0004)		(0.291)		(0.0004)		(0.229)			
	W	0.023	***	0.073	***	0.01	***	0.254		0.012	***	0.242	***	1,144	949
		(0.002)		(0.001)		(0.0005)		(0.264)		(0.001)		(0.052)			
	D	0.017	***	0.077	***	0.014	***	0.386		0.032	***	0.353	***	5.011	193
		(0.001)		(0.001)		(0.0006)		(0.366)		(0.002)		(0.04)			
4	Q	0.014	***	0.058	***	0.0041	***	0.247		0.003		0.243		167	6,721
		(0.005)		(0.002)		(0.0004)		(0.236)		(0.002)		(0.190)			
	M	0.018	***	0.061	***	0.0060	***	0.322		0.007	**	0.314	**	455	2,837
		(0.003)		(0.001)		(0.0005)		(0.217)		(0.003)		(0.125)			
	W	0.018	***	0.064	***	0.010	***	0.264		0.018	***	0.246	***	1,753	707
		(0.002)		(0.001)		(0.0007)		(0.252)		(0.001)		(0.039)			
	D	0.017	***	0.076	***	0.0134	***	0.319		0.047	***	0.272	***	7,291	167
		(0.001)		(0.001)		(0.0009)		(0.310)		(0.002)		(0.018)			
5 (Smallest)	Q	0.014		0.061	***	0.0042	***	0.689	**	0.001	**	0.688	***	122	10,499
		(0.013)		(0.006)		(0.0003)		(0.322)		(0.0004)		(0.156)			
	M	0.006		0.01	***	0.0063	***	0.301		0.003	***	0.298	**	308	3,742
		(0.007)		(0.002)		(0.0004)		(0.289)		(0.0002)		(0.148)			
	W	0.001		0.006	***	0.0102	***	0.329		0.009	***	0.320	***	1,203	1,008
		(0.005)		(0.001)		(0.0005)		(0.238)		(0.0004)		(0.055)			
	D	0.007	***	0.024	***	0.0134	***	0.372		0.022	***	0.350	***	5,673	250
		(0.002)		(0.001)		(0.0006)		(0.399)		(0.001)		(0.033)			

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 8: **Mean Contemporaneous and Time-Series Correlations of Purchase Intensities of Traders on SocialEx.** The first row of the table ($\tau = 0$) presents the monthly, weekly, and daily mean contemporaneous correlations in percent of the purchase intensities of two random groups of traders, G_1 and G_2. The other rows show the monthly, weekly, and daily mean temporal correlations in percent of purchase intensities in period t with the purchase intensities in period $t + \tau$. The t-statistics are calculated based on the mean and standard deviation of the correlations. For $\tau = 11$ the t-statisitcs for the monthly correlations of each group with itself cannot be computed due to the lack of degrees of freedom.

	Correlation of $\pi_{i,t}$ between months t and $t+\tau$			t-statistics			Correlation of $\pi_{i,t}$ between weeks t and $t+\tau$			t-statistics			Correlation of $\pi_{i,t}$ between days t and $t+\tau$			t-statistics		
τ	G_1 with G_1	G_2 with G_2	G_1 with G_2	G_1 with G_1	G_2 with G_2	G_1 with G_2	G_1 with G_1	G_2 with G_2	G_1 with G_2	G_1 with G_1	G_2 with G_2	G_1 with G_2	G_1 with G_1	G_2 with G_2	G_1 with G_2	G_1 with G_1	G_2 with G_2	G_1 with G_2
0	100	100	98.5	NA	NA	282	100	100	95.9	NA	NA	198	100	100	77.4	NA	NA	72.6
1	93	91.3	91.9	58.8	44	76.7	91.9	92.0	91.3	167	151	179	71.8	75.5	71.1	58.7	73.2	81.8
2	90.7	89.8	89.9	39.8	37.5	54.7	88.9	88.2	88.0	98.2	86.5	124	63.6	66.1	64.5	45.5	48.1	67.4
3	84.8	83.6	84.1	36.4	32.9	48.1	87.3	86.7	86.2	71.7	73.0	93.0	62.0	64.9	62.4	40.6	47.4	63.7
4	80.7	81.4	80.9	25.8	28.9	37.7	85.7	85.6	85.1	69.3	70.2	85.9	61.6	63.9	61.4	42.0	43.5	60.0
5	79.1	78.2	78.7	26.2	26.3	36.7	84.6	85.0	84.0	74.2	70.4	79.5	58.5	62.6	60.3	37.3	41.4	56.0
6	79.1	81.1	80	20.7	25.5	33.8	84.1	83.9	83.5	62.5	63.5	82.6	65.3	67.4	64.4	47.4	50.7	64.7
7	77.3	77.5	77.1	17.1	24	29.6	82.9	83.2	82.9	56.8	57.6	77.4	63.2	65.9	62.4	44.1	49.8	62.6
8	77.5	79.8	78.3	23.5	26.4	33.5	82.7	82.6	82.2	51.2	52.8	72.9	64.2	66.4	63.4	46.8	49.8	66.0
9	75.3	76.8	75.9	36.3	29.3	34.6	82.7	82.4	82.1	56.3	51.8	72.1	55.7	58.1	56.3	35.8	37.5	51.0
10	71.3	75.9	73	75.8	15.1	29	81.9	82.0	81.7	54.9	54.3	78.3	56.0	57.6	55.8	36.7	39.3	52.4
11	68.9	71.6	69.9	NA	NA	37.8	80.9	80.7	80.4	58.5	56.1	76.6	56.0	57.0	55.7	36.0	34.6	49.8
12							79.6	79.5	79.3	53.8	49.7	70.6	55.2	56.7	55.6	35.6	34.2	47.8
13							77.4	78.0	77.9	48.9	48.6	69.4	61.0	62.4	61.1	44.1	42.7	58.8
14							77.2	77.5	76.9	46.3	47.7	65.7	60.2	62.0	59.6	43.9	44.7	56.7
15							74.9	75.9	75.1	44.7	43.5	61.0	60.3	63.0	60.4	41.7	44.3	58.6
16							74.6	75.7	75.0	44.8	45.7	62.5	53.8	56.0	53.8	34.2	34.0	47.9
17							75.0	74.6	74.6	46.2	44.8	62.1	53.8	55.5	53.2	32.7	34.2	44.2
18							74.2	74.7	74.4	49.0	44.3	68.8	51.8	53.5	52.6	30.2	31.6	44.1
19							73.1	73.8	73.1	42.3	40.8	57.3	53.9	54.0	53.0	33.8	29.5	45.1
20							72.9	73.3	72.6	36.7	37.6	52.2	58.7	59.7	59.2	38.1	38.6	56.3
21							71.3	72.6	72.1	32.6	33.4	47.9	58.2	59.4	58.5	38.0	39.6	54.0
22							71.9	73.1	72.6	38.9	34.2	51.7	58.1	60.5	58.9	38.7	39.5	54.0
23							72.0	73.1	72.7	36.6	44.3	59.9	51.4	54.8	52.4	28.8	32.4	45.0
24							71.9	73.7	72.9	40.9	38.1	59.1	50.7	52.3	51.1	28.8	28.7	41.8
25							71.6	74.2	72.9	36.7	44.5	55.3	51.3	53.2	51.7	29.8	32.0	42.5
26							71.7	75.0	73.4	42.4	41.0	61.4	50.1	53.1	51.1	28.3	29.3	40.6
27							71.8	75.2	73.7	46.0	42.2	57.2	59.1	59.6	58.9	39.8	36.3	54.4
28							71.7	75.2	73.6	35.3	44.6	56.0	56.0	58.5	57.5	34.9	36.5	52.5
29							69.3	73.3	71.2	38.3	40.6	56.8	55.7	60.2	58.5	34.0	38.6	53.1
30							68.3	73.0	70.5	35.6	35.8	52.8	50.2	52.7	51.0	29.6	30.5	42.6
31							69.4	73.7	71.4	33.4	34.8	50.2	50.3	50.5	49.6	29.4	29.3	39.4
32							67.5	73.3	70.5	28.8	31.5	44.0	51.2	50.4	50.3	32.0	29.6	40.6
33							69.0	72.8	71.1	26.5	28.4	40.0	50.8	51.3	50.2	30.4	28.1	39.0
34							71.9	73.3	72.7	32.4	25.3	43.1	57.1	58.6	57.3	35.3	36.7	49.9
35							70.5	74.8	73.2	34.9	34.4	53.6	56.0	56.7	56.7	35.2	35.1	51.2
36							73.0	76.6	74.7	46.9	46.4	67.3	55.2	57.9	56.7	31.5	35.4	48.7
37							72.4	75.1	73.8	49.8	45.5	71.9	49.9	52.6	50.0	28.3	30.6	39.5
38							70.2	74.6	72.7	52.1	45.9	75.8	49.5	50.4	49.5	26.9	27.6	37.5
39							67.6	72.2	70.0	40.3	37.4	53.8	48.4	50.9	50.3	25.6	28.8	41.4
40							68.2	71.9	69.9	40.2	42.8	60.0	49.3	51.1	49.6	26.7	29.4	39.2

Table 9: **Mean Contemporaneous and Time-Series Correlations of Purchase Intensities of Traders on TradEx.** The first row of the table ($\tau = 0$) presents the monthly, weekly, and daily mean contemporaneous correlations in percent of the purchase intensities of two random groups of traders, G_1 and G_2. The other rows show the monthly, weekly, and daily mean temporal correlations in percent of purchase intensities in period t with the purchase intensities in period $t + \tau$. The t-statistics are calculated based on the mean and standard deviation of the correlations.

	Correlation of $\pi_{i,t}$ between months t and $t+\tau$			t-statistics			Correlation of $\pi_{i,t}$ between weeks t and $t+\tau$			t-statistics			Correlation of $\pi_{i,t}$ between days t and $t+\tau$			t-statistics		
τ	G_1 with G_1	G_2 with G_2	G_1 with G_2	G_1 with G_1	G_2 with G_2	G_1 with G_2	G_1 with G_1	G_2 with G_2	G_1 with G_2	G_1 with G_1	G_2 with G_2	G_1 with G_2	G_1 with G_1	G_2 with G_2	G_1 with G_2	G_1 with G_1	G_2 with G_2	G_1 with G_2
0	100	100	58.4	NA	NA	10.3	100	100	48.2	NA	NA	17.0	100.0	100.0	32.7	NA	NA	23.4
1	42.9	35.0	38.7	7.4	6.0	9.0	29.3	38.8	31.4	10.3	14.8	15.6	25.1	23.1	19.0	17.4	15.5	18.4
2	34.2	27.2	32.5	6.4	4.4	8.7	23.4	30.0	26.9	8.3	10.0	13.7	17.8	15.7	13.3	11.7	10.2	12.0
3	37.2	37.9	32.0	7.4	8.0	7.6	19.6	23.9	21.4	7.1	8.5	10.8	20.5	16.3	13.6	13.1	10.5	12.5
4	30.0	34.8	32.5	4.9	6.1	8.2	18.5	24.3	23.5	6.5	8.2	11.8	15.7	10.3	11.0	10.1	6.4	10.0
5	29.0	33.5	29.9	5.5	5.9	7.4	16.8	27.2	24.4	5.8	9.1	12.0	16.3	11.0	12.0	10.7	6.8	11.0
6	22.5	26.2	23.2	3.9	5.6	5.1	21.1	26.4	21.2	7.3	9.1	10.6	16.1	13.9	13.5	10.7	9.4	13.1
7	22.8	28.5	23.9	4.3	6.0	6.4	18.1	22.9	20.8	6.5	7.9	10.2	16.7	11.5	12.4	12.9	8.3	13.1
8	23.0	29.2	23.5	4.1	5.8	5.8	20.5	19.2	17.0	7.1	6.4	8.0	13.9	12.9	11.8	9.5	8.8	11.6
9	22.2	27.3	27.6	3.6	4.0	6.0	21.6	22.8	21.6	8.1	7.7	11.7	13.1	10.3	10.2	8.7	6.5	9.3
10	25.9	18.3	20.9	4.6	3.5	4.9	19.3	20.3	21.1	7.4	6.6	10.0	12.2	8.6	9.8	7.8	5.7	8.8
11	24.0	25.7	22.1	4.3	4.4	5.4	16.0	23.6	20.1	6.2	8.7	10.3	13.2	10.8	10.7	8.7	7.0	9.8
12							16.3	22.9	19.6	5.9	9.1	9.4	13.4	10.5	10.8	8.8	6.8	9.9
13							18.3	22.9	20.3	6.5	7.5	9.7	14.0	11.3	12.4	10.1	7.6	12.1
14							21.5	27.4	21.2	7.2	10.0	10.5	12.8	9.6	10.9	10.0	6.8	11.2
15							19.6	24.6	21.7	7.0	8.3	10.4	13.8	12.2	10.1	9.2	8.4	9.6
16							22.4	25.7	21.3	7.9	8.9	10.5	12.1	11.2	9.1	7.8	7.5	8.2
17							21.5	23.8	22.0	8.0	8.4	10.6	11.6	6.9	10.1	7.6	4.3	9.2
18							15.1	21.3	18.2	5.3	7.6	8.8	8.3	9.4	8.6	5.1	6.0	7.6
19							21.1	20.8	21.4	7.7	7.0	10.8	10.7	7.3	7.5	7.0	4.6	7.0
20							16.2	21.5	19.2	5.0	7.4	9.5	11.5	6.5	9.3	7.8	4.3	9.2
21							16.0	21.5	18.9	5.2	7.7	8.8	9.9	7.9	8.8	7.4	6.0	9.3
22							16.8	17.7	17.3	6.1	5.8	8.7	9.7	9.7	8.1	6.4	6.6	7.8
23							22.5	17.0	16.2	8.4	5.7	7.9	7.7	9.3	7.8	5.0	6.0	7.2
24							15.7	19.2	16.6	5.4	6.5	8.2	8.4	8.8	8.9	5.4	5.7	8.3
25							20.1	16.7	14.1	7.2	5.6	7.0	9.0	11.4	11.4	5.9	7.2	10.5
26							13.5	16.5	14.4	4.6	5.8	7.4	8.7	7.8	6.9	5.6	5.1	6.2
27							9.8	11.8	14.0	3.4	4.0	7.1	10.4	7.1	9.5	6.9	4.9	9.2
28							15.5	14.6	14.6	5.0	4.9	7.0	10.8	8.1	10.1	8.0	6.1	10.7
29							14.2	16.2	15.2	5.0	5.5	7.5	8.8	7.4	7.8	5.9	4.9	7.4
30							11.2	16.7	14.8	3.8	5.6	7.1	9.8	9.2	8.8	6.3	5.9	8.2
31							14.9	19.7	15.1	4.8	6.7	7.2	9.6	9.0	10.6	6.1	5.7	9.7
32							13.5	15.4	13.2	4.6	4.8	6.0	8.8	7.7	9.1	5.8	5.0	8.2
33							12.9	20.2	16.9	4.0	7.4	8.2	9.9	8.4	8.8	6.4	5.2	7.8
34							14.7	19.1	13.5	4.7	5.9	5.9	12.0	11.3	10.0	8.6	7.4	9.4
35							14.9	18.6	17.5	4.7	7.1	8.9	12.2	8.9	9.9	9.0	6.6	10.2
36							17.0	20.0	18.0	6.3	6.7	8.4	8.5	11.6	11.2	5.7	7.8	10.9
37							14.5	17.6	13.3	4.6	5.4	6.0	9.7	11.2	9.5	6.4	6.9	8.7
38							17.0	22.1	18.8	5.8	7.6	8.2	9.3	9.4	9.0	6.0	6.1	8.1
39							13.6	20.6	15.3	3.9	6.6	7.1	7.0	7.9	9.5	4.5	5.1	8.7
40							15.1	14.1	17.8	5.0	4.6	8.4	8.1	8.0	8.2	5.0	5.2	7.6